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STATE OF THE ART OF STRUCTURAL HEALTH MONITORING OF WIND TURBINES

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ABSTRACT

In the search for a sustainable and clean alternative to fossil fuel, renewable energy sources, specifically, wind energy is seen to possess immense potential with a lot of scope for improvement. Wind energy systems, using rotating blades, convert the kinetic energy of winds into other forms of usable energy like electrical or mechanical energy. The most essential part of these systems is the wind turbine. The dependability of these wind turbines directly correlates to obtaining the maximum quantity of energy from the available wind source, resulting in an increase in the overall efficiency of energy generation. However due to varying environmental conditions, defects and damages are unavoidable creating the urgency for new and innovative maintenance strategies to ensure system's safety, profitability and cost-effectiveness. Techniques such as structural health monitoring (SHM) and fault diagnosis system (FDS) have proven to be imperative in the pre-emptive detection of faults in the wind turbine. These techniques facilitated a proactive feedback mechanism, reduced downtime of the systems thereby increasing its productivity. This study reviewed various strategies, methodologies and machine learning algorithms developed for monitoring of wind turbine performance and early fault detections in these turbines. Additionally, a novel, state-of-the-art technique using SHM and FDS for diagnosis on wind turbines is also presented. This study is an extended work of Márquez et al (2012).

***KEYWORDS:** Wind Turbine, Fault Diagnosis, Structural Health Monitoring & Machine Learning*

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Original Article

1. INTRODUCTION

The ability to generate electricity using the naturally flowing winds in the earth's atmosphere is wind power. The wind turbine is used to draw wind energy from the flow of wind and converts the kinetic energy possessed by these winds into other forms of useable energy mainly for electricity generation. Wind energy is a form of renewable energy that is clean, and available in abundance. Moreover, due to the looming threat of fast depletions and rising costs of fossil fuels in the past few decades, energy generation from various renewable energy sources has been on the rise. Being cost effective and pollution-free, solar and wind energy have proven to be highly sustainable forms of energy generation with ever increasing potential.

There are three major types of wind power [1]. They are utility-scale wind, which uses wind turbines that are in the size range of about 100 Kilowatts to several Megawatts. Electricity is delivered to the main power grid and with the assistance of electric utilities or power system operators, it is later distributed to the end user. Secondly, distributed or small wind, which uses turbines of 100 kilowatts or lesser. Their primary use is to

power a small business or farmland, or a small household. Lastly, offshore wind, used to drive wind turbines that were erected in large water bodies across the globe [2].

The primary distinction between wind-based power generation and sunlight-based power is the season of availability and accessibility. Albeit both are irregular, wind control is accessible for the duration of the entire day whereas solar power is limited to just amid the day for obvious reasons [3]. This has genuine ramifications for dispersing power as power utilization goes on at all times, day and night. In excess of 54 GW of clean sustainable breeze control was brought into the worldwide market in 2016. Presently, it contains more than 90 nations, incorporating 9 countries with an excess of 10,000 MW introduced, and 29 of which have now moved past the 1,000 MW stamp. The combined limit developed by 12.6% to achieve a sum of 486.8 GW [4]. Wind power generation is currently rivalling the heavily sponsored officeholders over the globe, assembling new ventures, providing countless job opportunities and is well on its way to becoming vital for a sustainable future. GWEC's moving five-year figure saw right around 60 GW of new breeze control plant establishments in 2017, ascending to a yearly market of around 75 GW by the year 2021, to bring the aggregate introduced limit to a staggering 800 GW or higher before the close of 2021.

Figure 1: Market Forecast for 2016–2020 Which was Presented by GWEC.

2. NEED FOR SHM AND FDS

Yearly activities, maintenance and support costs for wind turbines, which incorporate protection, consistent upkeep, repair, save parts, and organization, were approximated to be 3% to 5% of the aggregate cost of the establishment. An alternate assessment demonstrates that costs are proportional to about 20% of the cost for a kilowatt-hour created over a 20-year lifetime cycle of the turbine. In an event that the turbine is in its early years, the expenses reach to about 10–15%. However, this reaches a staggering 20–35% towards the latter part of the turbine's life cycle [5]. Maintenance, expenses for repair and extra parts, in particular, increment as the turbine get older. As per the 2010 Wind Technologies Market Report, discharged in June 2011 by the United States, Bureau of Energy and the Lawrence Berkeley National Laboratory, regardless of constrained information accessibility, it gives the idea that the recently introduced activities have, on a normal, brought down maintenance and support costs in a far more impactful manner when compared to the more seasoned undertakings in their initial phase with lot of activity resulting in tasks and upkeep costs increment as ventures age [6–8]. Inside the breeze vitality framework, certain parts may require a more basic task and administration mentality than others. Singular segments that are more inclined to develop faults and are basic to turbine functioning are more costly or tedious to repair [9].

Upkeep incorporates any activities suitable for holding the gear in or re-establishing it to a given condition. Support is required to guarantee that the parts keep on performing to the capacities for which they were made, i.e. to their best efficiencies. The primary goals of the upkeep movement are to

- Convey the base assets that are required
- Guarantee framework unwavering quality
- Quick response and recoup from breakdowns

The connected upkeep methodology can be either preventive or restorative. If an anticipated fault is avoided and kept away from, it acts in a preventive manner. When a recognized or detected fault is repaired, it acts in a restorative manner [10]. Condition checking is performed in three fundamental advances:

- Information procurement utilizing sensors
- Flag handling utilizing different information preparing methods
- Highlight extraction through the recovery of attributes that will help in setting up the present status of the observed hardware.

Utilizing of both, the current data sources and the data on past statuses of the framework taken from put-away information, the current situation of the framework is acquired and checked for blame identification or forecast. After a blame is analysed, remedial or restorative upkeep is carried out [11].

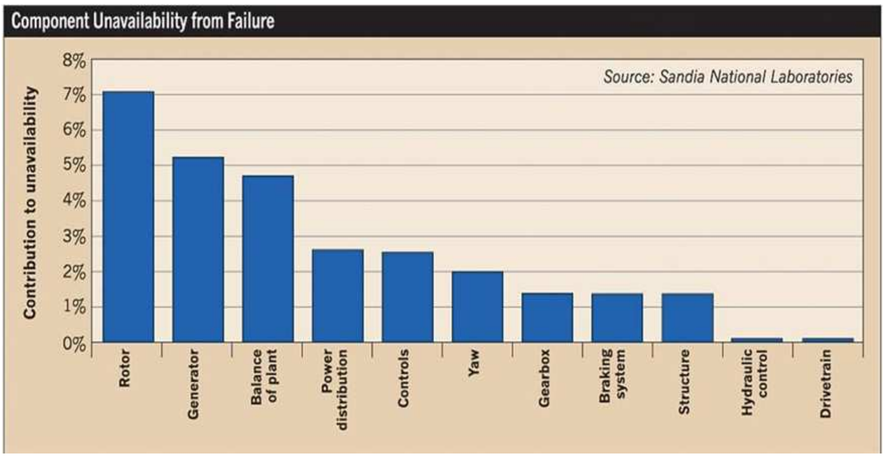

Figure 2: Failure Percentage Rate in Wind Turbine (Sandia National Laboratories).

Despite the fact that there are a variety of segments depending on the maker, arrangement, and working conditions, certain things, for example, generators, control converters, and various gearboxes have been specifically chosen as faults inclined by specific investigations. As per a report created by Sandia National Laboratories, the continuous reliability enhancement for wind (CREW) database discoveries, state the three best supporters of turbine inaccessibility to be cutting/rotor edges, electric generators, and adjustment of plant (tower), as appeared in Figure 2. Two ways to implement restorative upkeep can be recognized, (i. e) palliative support, which comprises of temporary answers for the faults, and remedial upkeep to the standing answers for the faults [12]. In the event that a fault is anticipated, preventive upkeep is completed before the fault can happen. For this situation, four unique methodologies can be utilized:

- Planned upkeep or time-based
- Current-state based or restrictive support
- Anticipating support or parameter-projection-based
- Status-based or proactive support

As indicated by the Swedish standard SS-EN 13306, monitoring is characterized as a movement performed physically or naturally, with the intention to watch the genuine condition of a thing [13].

The key criteria that determines the utility of any condition checking framework would be to give a solid sign of the nearness of a blame inside the breeze vitality change frameworks (wind energy conversion systems - WECS) and to demonstrate the area and seriousness of the circumstance. As a solution, a condition checking framework is needed, for early cautioning sign recognition [14]. Condition observing is greatly dependent on information procurement and preparation of signs. This can be actualized by utilizing different methodologies with various levels of innovation. The subsystem-level condition observing of wind turbines depends on various subcomponents identified with nearby parameters and empowers the obtaining of data on particular segments and therefore improves the exact restriction of inevitable faults. Wind turbines are automated, remote power plants, and therefore different from most traditional power stations. Hence, they are subjected to exceedingly varying and brutal climate conditions. These range from quiet to serious breezes, lightning, tropical warmth, ice, hail, and snow. Due to these testing external factors, wind turbines sharp edges experience continually evolving loads, which lead to very stressful working conditions that prompt serious mechanical pressure [15].

A preventive upkeep technique that avoids machine shutdown and downtime can extensively bring down these expenses. In this way, turbine blade cutting edges require an expert level of support and maintenance to give a protected, practical, and solid power yield with worthy gear life [16]. A highly impactful in class technique for deciding the support procedure in the wind turbine industry is solid upkeep. This comprises mainly of two important tactics - preventive support in light of execution along with parameter observing and ensuring activities. In this system, condition checking is utilized to decide the ideal point amongst remedial and planned support procedures [17]. Figure 3 (Tchakoua et al, (2014)) [18] presents the traditional condition monitoring flowchart.

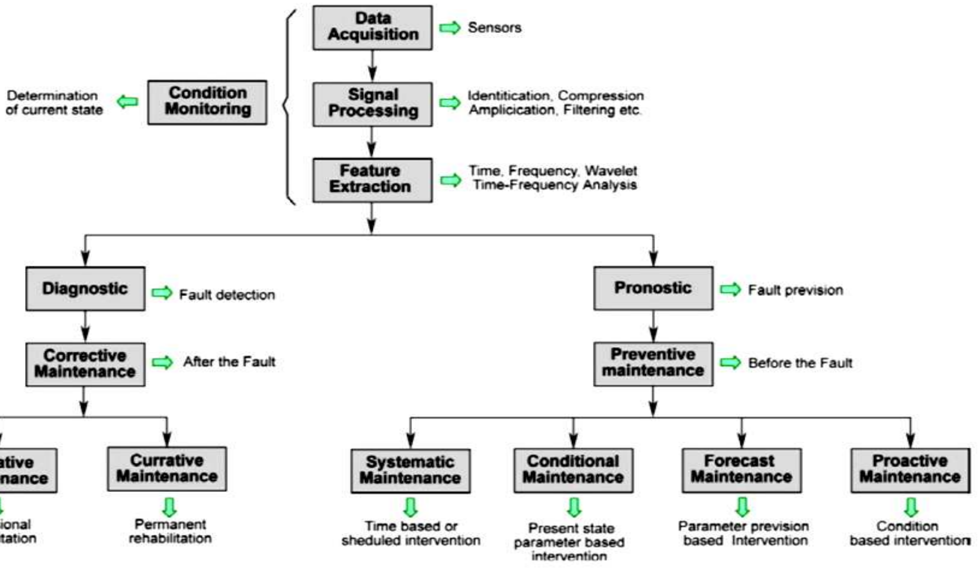

Figure 3: Condition Monitoring Flowchart.

3. TECHNIQUES FOR SHM AND FDS ON WIND TURBINES

There are various strategies and techniques which can be adopted for recognizing the faults in wind turbine. On this premise, a noteworthy change is characteristic of creating a fault [19]. SHM and FDS contain various combinations of sensors and flag handling gear that gives consistent health signals of parts. Subsequently, the condition of the wind turbine can also be analysed using some novel methods including acoustics, vibration investigation, oil examination, thermography and strain estimation. On wind turbines, these methods are utilized to screen and monitor the status of system-essential segments and to analyse their working condition. These include but are not limited to, the cutting edges, gearbox, generator, direction and tower. Observing might be on-line (i. e) and henceforth give immediate criticism of condition or disconnected (i.e) information being gathered at normal time interims utilizing estimation frameworks that are not incorporated with the hardware [20]. With efficient information procurement and suitable flag preparing, shortcomings would thus be able to be recognized and predicted while segments are still operational and proper preventive measures can be arranged so as to forestall faults to the essential parts and subsequent harm to the system. Support and maintenance actions can then be arranged and planned with more effectiveness, bringing about increased quality of power generation, better accessibility, and improved security. Together, these improvements will cause a reduction in downtime, upkeep and operational expenses, resulting in an overall increase in efficiency of power generation [21]. SHM and FDS strategies are in this way utilized throughout the business [22] and benefits are particularly more for seaward wind farm(s) [23]. This is due to the higher expenses of task and support adrift and the larger sizes of turbines. As explained earlier, there are various methods and techniques that are implemented to monitor the condition of wind turbines. These are:

3.1 Vibration Analysis

Vibration examination is a very popular innovation in the world of fault diagnosis. This technique is utilized regularly in wind turbines, particularly to rotatory gears [24]. A large variety of sensors are needed for various frequencies, and position transducers are utilized for low-recurrence run; speed sensors in the central recurrence region; accelerometers in the high recurrence run and ghastly transmitted vitality sensors for the higher frequencies [25]. Through vibration flags, various essential segments of the wind turbine system can be monitored, like checking the cutting edges [26], the gearbox [27], and the course [28] et cetera, and thus the state of the system can be analysed and diagnosed if needed.

3.2. Acoustic Emission

Rapid arrival of strain vitality happens after which versatile waves are created. This occurs when the structure of the metal is adjusted, and is examined by acoustic emanations (AE). The essential wellsprings of acoustic emanations in wind turbines are the age and proliferation of splits, and the strategy is found [29] to recognize a few faults sooner than others, for example, vibration examination [30]. The utilization of acoustic emanations is slowly but surely developing for both SHM and FDS of turning wind turbine parts and additionally sharp edges.

3.3. Ultrasonic Testing Techniques

Ultrasonic testing (UT) procedures are utilized widely by the breeze vitality industry for the basic assessment of wind turbine towers and cutting edges. Ultrasonic testing is largely utilized for location and subjective evaluation of surface and subsurface basic imperfections [31, 32]. Ultrasonic wave spread attributes allows for the estimation of the area and the kinds of surface imperfections present. Thus, UT gives a dependable strategy for deciding the material properties of the central turbine parts [33–35].

3.4. Oil Analysis

Regardless of whether there is a definitive reason for ensuring quality of oil or the state of the different moving parts, the oil examination is regularly carried out on a disconnected system by taking examples [36] in spite of on-line sensors having (for a considerable length of time) been accessible at an adequate value level [37] for checking oil temperature, defilement and dampness [38]. On account of inordinate channel contamination, oil defilement or a change in segment properties or the portrayal of the particulates can lead to signs of unnecessary wear [39, 40].

3.5. Strain Measurement

Strain estimation utilizing strain measures can be exceptionally helpful for time anticipating and ensuring against high-feelings of anxiety, particularly on the edges. An evaluation of the strain check flag obtained from the strain measure sensors introduced on the edge of the blade has been performed. A specific end goal was kept in mind, to alter alignment practices and sensor choices [41–43]. Strain estimation can be relied upon to develop significantly and have a very impactful contribution to SHM.

3.6. Electrical Effects

SHM of electrical gear, for example, engines, generators, and collectors is normally performed with the help of voltage and current examinations. Release estimations are utilized for medium to high voltage matrices. A spectral examination of the stator current [44] present in the generator is utilized for distinguishing detachment faults occurring in the cabling without affecting the working of the wind turbine. References [45, 46] exhibit how the opposition standard is helpful for identifying weakness harm specifically.

3.7. Shock Pulse Technique

The shock-pulse technique has been utilized as a strategy for condition checking of direction. It works by identifying the mechanical stuns created when a roller or ball in a heading interacts with harmed territory of the raceway or with flotsam and jetsam [47, 48]. The technique is utilized occasionally in order to help with vibration estimations.

3.8. Process Parameters and Performance Monitoring

The relationship among parameters [49–51], for example, control, wind speed, rotor speed and cutting edge point can similarly be utilized for the evaluation of wind turbine condition as well as for the early identification and prediction of issues and faults [52, 53]. Like approximation of process parameters, more modern techniques, including drifting, are not regularly utilized [54].

3.9. Radiographic Imaging/Inspection

Radiographic inspection or imaging of basic turbine segments utilizing X-ray is also rarely relied upon despite the fact that it provides helpful data with respect to the basic state of the part being assessed [55]. A transportable radiographic framework for wind turbines sharp edges is exhibited lately, as a solution for identifying surrenders and decreasing the cost of investigations [56].

3.10. Thermography

Thermography is regularly utilized for observing electronic and electrical segments and recognizing faults in systems [57, 58]. The procedure usually includes visual elucidation of problem areas that emerge due to bad contact or framework

faults. [59]. An early examination of complete thermographic estimations of in-benefit edges utilizing helicopters to convey the Infra-Red cameras is yet to be demonstrated tastefully and often faces troubles in execution [60].

4. SENSOR DATA AND SIGNAL PROCESSING FOR WIND TURBINES

Aside from the procedure, the capability and efficiency of SHM and FDS depend upon two fundamental components: the number and kind of sensors, and the related flag handling and disentanglement strategies used to extract important data from the various signs. An electronic estimation framework will procure the information and further circulate them to an eyewitness or other specialized control frameworks. Information obtaining will include estimating the required factors (e.g. voltage, temperature, current, speed) and converting them into electronic signals [61, 62].

4.1. Statistical Methods

One fundamental usage of measurable calculations for the motivations behind SHM is to investigate the information signals from the different sensors in wind turbines [63, 64]. Basic factual estimates, like root mean square (RMS) and pinnacle adequacy are broadly utilized for the identification of faults; in any case, further developed highlights are additionally being created. Additional important statistical parameters are the mean, median, mode, skewness, shape factor, standard deviation, peak-to-peak, crest factor, maximum value, minimum value, range, sum, sample variance, energy ratio definite integral, impulse factor and kurtosis [65].

4.2. Trend Analysis

At the point when connected to wind turbine, drift examination alludes to the idea of gathering information from the different sensors and searching for patterns. It requires specific calculations [66, 67], and applications incorporate the observing of pitch systems albeit the most basic is its utilization on control yield designs from wind turbine generators.

4.3. Filtering Methods

Sometimes there is repetitive information with redundant data. These must be filtered out in order to abstain from trading off the calculations and increasing computational time [68, 69]. The downside of sifting while checking patterns is that the parameters must be changed in accordance to the differing working conditions after careful considerations.

4.4. Time-Domain Analysis

Analysis done in the time domain is another method of monitoring wind turbine fault like inductive and resistive imbalances present between the rotor and the stator phases as well as turn to turn faults present in the rotor windings of the generator.

4.5. Cepstrum Analysis

The power cepstrum is a period-based approach characterized as the converse Fourier change of the logarithmic power range [70]. The cepstrum is appropriate for methods to gear diagnostics on a wind turbine. Rigging vibration spectra normally indicate sidebands of cross section recurrence and its music emerging from the adjustment of tooth fitting waveform [71, 72].

4.6. Time-Synchronous Averaging

Commonly known as time-domain averaging, it is a technique used for signal processing, that serves as the foundation for various gear fault detection algorithms. The technique is used for recognizing a turning bearing deformity by estimating the vibration of a pivoting bearing and acquiring a waveform signal [73, 74].

4.7. Fast-Fourier Transform (FFT)

The FFT [75] calculation is utilized for the change of a computerized motion from the time domain into the frequency domain. Specific recurrence ranges relate to specific conditions the reaches mirroring the rotational speed of the principle shaft and the shape and the extent of the component concerned [76, 77].

4.8. Amplitude Demodulation

This method can separate low-adequacy and low-recurrence occasional signs that may be conceal by other higher vitality vibrations as in wind turbine gearboxes [78]. While the crude range can be valuable for checking gear work frequencies, the envelope range gives better affectability than bearing imperfection frequencies in wind turbine applications [79].

4.9. Order Analysis

FFT is helpful for examining motions in consistent speed wind vitality converters when connected to time arrangement signals. However, this calculation isn't reasonable for variable speed wind vitality converters where an alternate calculation in light of rotational edges is required, (i. e) alleged request examination, especially appropriate for rotor uneven characters and streamlined asymmetries [80].

4.10. Wavelet Transforms

This is a time-frequency technique like Short-Time Fourier Transforms yet more suitable for non-stationary signs. It gives a period recurrence 3D guide of the signal being dissected in [81] and includes disintegrating it into an arrangement of sub-signals and levels with various frequencies [82–87].

5. MACHINE LEARNING FOR WIND TURBINES

'Machine learning is the subfield of computer science that gives computers the ability to learn without being explicitly programmed' - Arthur Samuel (1959). Machine learning has risen from patterns and pattern recognition studies and artificial intelligence based computational learning theories. It dwells into the study and architecture of algorithms that analyse and study from data, learn from it and proceed to make predictions based on the same [87–90]. Machine learning (ML) is employed in a huge range of computing tasks. These computing tasks require designing and programming explicit algorithms with high performance and ML is used here as traditional methods are tasking and not feasible. Machine learning can be classified into three main categories: unsupervised learning, reinforcement learning and supervised learning. Using ML, the wind turbine fault diagnostic classification was carried out in three phases. They are feature extraction, feature selection and feature classification [91–96]. Feature extraction is a term for approaches of constructing combinations of the variables to get around problems while still being able to describe the required data with sufficient accuracy. Feature selection was the process of defining and choosing the most dominating features from these extracted features [97]. Feature classification was then carried out using machine learning classifiers using the selected features as the inputs to the classifiers [98–100]. The data model built was used for the SHM and FDS of a wind turbine [101, 102].

Recently, some findings using machine learning have been proposed for the wind-turbine application. To name a few, Jiménez et al, [103] performed a study on wind turbine blades maintenance management for blade delamination problem using machine learning classifiers like quadratic discriminant analysis (QDA), decision tree complex, weighted k-nearest neighbours and artificial neural networks. In this study, the autoregressive Yule–Walker model was used to carry out the feature extraction and Akaike's information criterion for the feature selection and obtained a maximum

classification accuracy of 91.5% for artificial neural networks. Detection of faulty high-speed wind turbine bearing was carried out by Elforjani et al, using signal intensity estimator technique [104]. In this study, crest factor and kurtosis (CF and KU) were reported as very sensitive statistical indicators when the presence of the defects occurred, as their values could go quite low to the level of undamaged components when the damage was well advanced. Colone et al, [56] have carried out a work on mass detection, localization and estimation for wind turbine blades that was based on the recognition of statistical patterns. In this study, the first test decided whether there was a significant mass change and the following test was a statistical group classification which was based on the method of linear discriminant analysis. Frequencies were identified by the means of an analysis called operation modal analysis and this was done using natural excitation.

Díaz et al, [105] carried out a performance assessment of five measure-correlate-predict (MCP) models for the estimation of long-term wind turbine power outputs. These wind turbines were at a target site, and Diaz et al, used three machine learning techniques, namely Random Forest (RF) artificial neural network (ANN), support vector machine for regression (SVR). They concluded that, out of the five MCP models used for comparison, the one that separately estimated wind speeds and air densities and later predicted the wind turbine power outputs always showed superior mean absolute error, mean absolute relative error and coefficient of determination metrics, independently of the target station and type of wind turbine under consideration. A study on wind turbine blade damage detection was done by Regan et al, using supervised machine learning algorithms [88]. This paper described the selection of a set of statistical features which were for acoustics-based damage detection of enclosed cavities present in wind turbine blades. A systematic approach was followed where machine learning algorithms like logistic regression and support vector machine methods were identified. These were then used along with optimal feature selection for decision-making via binary classification algorithms. Ali and Jaouad [90] carried out a work on multi-agent system which was based on the fuzzy control and extreme learning machine for intelligent management in a hybrid energy system. In this paper, they presented a multi-agent system based on wind and photovoltaic power prediction. They used neural networks trained by extreme learning machine algorithms, in order to estimate the total output produced by photovoltaic panels and wind turbines, in the form of photovoltaic and wind energy respectively.

Jiménez et al, [106] carried out an analysis on dirt and mud detection and diagnosis on a wind turbine blade which employed guided waves and supervised learning classifiers. It used a novel approach that took into account advanced signal processing and machine learning to identify the thickness of the dirt and mud present on the wind turbine blade. Initially, the signal was filtered by Wavelet transform. For feature extraction, they employed an auto regressive model (AR) and also used principal component analysis (PCA) and then utilized neighbourhood component analysis (NCA) for the feature selection. These were employed in order to filter out redundant and non-useful features and data. The machine learning classifiers like ensemble subspace discriminant, k-nearest neighbours, linear support vector machine, linear discriminant analysis and decision trees were used.

Using unsupervised machine learning, an online automatic diagnosis under real experimental conditions was done, on wind turbine bearings' progressive degradations by Ali et al, [107]. In this study, adaptive resonance theory 2 (ART2) was suggested for an unsupervised classification of the extracted features and the Randall model was adopted. This was done after taking the geometry of the tested bearing to train the ART2 in the offline step, into consideration. Cocchi et al, [108] did a case study on machine learning methods for short term bid forecasting in the renewable energy market in Italy. They considered the difficulty of predicting the sum of the bid volumes for wind energy of all the

producers, inside the day-ahead energy market. Lu et al, [109] performed an assessment of data-driven, machine learning techniques that can be used for machinery prognostics of offshore assets. They provided a novel design for the early fault detection on offshore wind turbines using machine learning.

Elforjani and Shanbr [110] used supervised machine learning to carry out a prognosis of bearing acoustic emission signals. In this study, support vector machine regression (SVMR), multilayer artificial neural network (ANN) model and Gaussian process regression (GPR) were used to correlate acoustic emission features with the corresponding natural wear of slow speed bearings. Ouyang et al, [111] did a work on predictive model of yaw error in a wind turbine through machine learning classifiers like support vector machine (SVM), neural networks (NN), random forest algorithm (RFA) and gradient boosted regression trees (GBRT). Dervilis et al, [112] carried out a review work on health monitoring of wind turbines, including the current and future trends followed by an active learning twist. They summarized the machine learning algorithms which were used in the condition monitoring of wind turbine. Peng et al, [113] put forward a novel probabilistic wind speed forecasting model. This was based on the combination of the adaptive ensemble of on-line sequential ORELM (Outlier Robust Extreme Learning Machine) and TVMCF (time-varying mixture copula function). From the above mentioned studies, one can conclude that machine learning (ML) has become the new automated approach for SHM and FDS on wind turbines for identifying faults on a wind turbine while it is in working condition.

6. CONCLUSIONS

Wind turbine technology has seen huge advancements in a relatively short period of time. Among the various methods and algorithms transferred from applications in other industries, SHM and FDS enable the prior detection and diagnosis of possible failures of essential components of the wind turbine system. This now serves as a platform for implementing condition monitoring practices, resulting in the arrival of a new epoch, with Machine Learning spearheading the way, for the predictive and preventive strategies on these systems. This paper has reviewed the state-of-the-art strategies currently prevalent for the structural health monitoring and fault diagnosis system of wind turbines. It also highlighted the statement that preventive and reactive maintenance used in a combinatory manner can improve dependability, accessibility, and upkeep of wind turbines. This results in reduction in maintenance costs, thus increasing the overall cost efficiencies related to wind turbine energy generation. A summary of SHM adds of the maintenance processes surrounding these wind-turbines and the multitude of techniques, concepts along with an extensive review of FDS techniques and methods were presented. Machine learning has become one of the essential tools for monitoring the wind turbine condition, and these can be applied to any type of wind turbine for off-line and on-line monitoring as an intelligent system.

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